Automated detection of individual clove trees for yield quantification in northeastern Madagascar based on multi-spectral satellite data

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Abstract: There is an increasing demand for clove products, mainly dried buds and essential oil on global markets. Consequently, the importance of clove trees as a provisioning service is increasing at the local level, particularly for smallholders cultivating clove trees as cash crops. Due to limited availability of data on local production, using remote sensing-based methods to quantify today's clove production is of key interest. We estimated the clove bud yield in a study site in northeastern Madagascar by detecting individual clove trees and determining relevant productio n systems, including pasture and clove, clove plantation and agroforestry systems. We implemented an individual tree detection method based on two machine learning approaches. Specifically, we proposed using a circular Hough transform (CHT) for the automated detection of individual clove trees. Subsequently, we implemented a tree species classification method using a random forests (RF) classifier based on a set of features extracted for relevant trees in the above production systems. Finally, we classified and mapped different production systems. Based on the number of detected clove trees growing in a clove production system, we estimated the production system-dependent clove bud yield. Our results show that 97.9% of all reference clove trees were detected using a CHT. Classifying clove and non-clove trees resulted in a producer accuracy of 70.7% and a user accuracy of 59.2% for clove trees. The classification of the clove production systems resulted in an overall accuracy of 77.9%. By averaging different clove tree yield estimates obtained from the literature, we estimated an average total yield of approximately 575 tons/year for our 25,600 ha study area. With this approach, we demonstrate a first step towards large-scale clove bud yield estimation using remote sensing data and methodologies.

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ABSTRACT

There is an increasing demand for clove products, mainly dried buds and essential oil on global markets. Consequently, the importance of clove trees as a provisioning service is increasing at the local level, particularly for smallholders cultivating clove trees as cash crops. Due to limited availability of data on local production, using remote sensing-based methods to quantify today's clove production is of key interest. We estimated the clove bud yield in a study site in northeastern Madagascar by detecting individual clove trees and determining relevant productio n systems, including pasture and clove, clove plantation and agroforestry systems. We implemented an individual tree detection method based on two machine learning approaches. Specifically, we proposed using a circular Hough transform (CHT) for the automated detection of individual clove trees. Subsequently, we implemented a tree species classification method using a random forests (RF) classifier based on a set of features extracted for relevant trees in the above production systems. Finally, we classified and mapped different production systems. Based on the number of detected clove trees growing in a clove production system, we estimated the production system-dependent clove bud yield. Our results show that 97.9% of all reference clove trees were detected using a CHT. Classifying clove and non-clove trees resulted in a producer accuracy of 70.7% and a user accuracy of 59.2% for clove trees. The classification of the clove production systems resulted in an overall accuracy of 77.9%. By averaging different clove tree yield estimates obtained from the literature, we estimated an average total yield of approximately 575 tons/year for our 25,600 ha study area. With this approach, we demonstrate a first step towards large-scale clove bud yield estimation using remote sensing data and methodologies.

1. Introduction

Obtaining statistical information about crops is of broad interest. In developed countries, where industrial agriculture is the dominant form of farming (Bowler, 2014), this information is often available due to official data collections and close monitoring of the crops by the farmers. Thus, relatively accurate projections about crop health and yields are possible. However, there are often no agricultural census data or agricultural statistics available in less developed countries. Smallholder farms, which are the dominant form of farming in less developed countries and which account for 85% of farms worldwide, are not officially overseen, and thus, information about their crop production is rarely available and is often inaccurate (Nagayets, 2005). Furthermore, smallholder farmers mostly produce for subsistence purposes which makes capturing this kind of data an even greater challenge. Thus, it is highly relevant to find methods to collect large-scale information about this often remotely located crop production.

Remote sensing offers a viable approach to gain insights about cultivated crops on a large scale (Nellis et al., 2009). One can gather information about plant traits and plant health (Homolová et al., 2013; Asner et al., 2015) or about crop distribution and yield (Lobell et al., 2015, Battude et al., 2016, Azzari et al., 2017).

In this paper, we use remote sensing to analyze clove production systems in northeastern Madagascar. Cloves (*Syzygium aromaticum*) are mainly produced in Indonesia, Madagascar and Tanzania (Lobietti, 2013). The two main products from clove cultivation are the dried flower buds and the essential oil (Danthu et al., 2014). As the global demand for both of these products is rising, cloves are of increasing

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importance on global trading markets (FAOSTAT n.d.) and for the national economies of the producer countries. This is especially true for Madagascar, which is the second largest producer and even the leading exporter of cloves worldwide (FAOSTAT n.d.). The increasing global demand for cloves makes their cultivation also more important at the local scale (Danthu et al., 2014), whereby the Madagascan smallholder farmers often aim to generate revenue with the cultivation of cloves, next to coffee and vanilla, as cash crops (Lobietti, 2013; Danthu et al., 2014; Thomson, 2016).

Several studies have successfully shown the potential of individual tree detection or tree crown delineation in temperate and boreal forests (Gougeon and Leckie, 2006; Hirschmugl et al., 2007; Wolf and Heipke, 2007; Wang, 2010; Kaartinen et al., 2012). Others have focused on detecting specific trees in orchards or plantations (Daliakopoulos et al., 2009; Aksoy et al., 2012; Srestasathiern and Rakwatin, 2014; Mahour et al., 2016; dos Santos et al., 2017; Koc-San et al., 2018). Nevertheless, delineating individual trees in tropical forests is a challenging task that is mainly hindered by closed canopies and the large variability of crown shapes and sizes (Clark et al., 2005; Baldeck et al., 2015).

A reliable method to detect and delineate individual trees is also important for tree species classification (Baldeck et al., 2015). Several studies have already successfully classified different tree species based on remote sensing data (e.g., Pouliot et al., 2002; Ørka et al., 2009; Dalponte et al., 2012; Shang and Chisholm, 2014). For tropical forests, however, an automated tree species classification is a mainly unresolved problem (Baldeck et al., 2015). In addition to facing the challenge of hampered tree delineation to obtain spectrally pure training data, one of the major challenges in tropical forests is the extremely high species diversity of sometimes more than 300 species per hectare (Baldeck et al., 2015). Thus, classification approaches used for temperate forests cannot be easily adapted to tropical forests. Although there are several studies demonstrating the ability to distinguish and properly classify several species in tropical forests based on their spectral differences, spatially mapping these species still remains a challenge (Clark et al., 2005, Immitzer et al., 2012, Asner et al., 2015). The investigated species could be distinguished from each other but not from the many other spectrally unknown species surrounding them. Baldeck et al. (2015) have identified a potential cause of the above challenge in the classification approach itself. All of these studies used a multi-class classification approach, which requires very large training sets to achieve high accuracy when dealing with many classes. Instead, Baldeck et al. (2015) proposed a single-class classification approach, as this kind of approach improves classification accuracy for the focal class and not the average accuracy for all the model classes (Aly, 2005). Nevertheless, this approach is not limited to one species, but several species can be classified by combining the single-class models of different species. Baldeck et al. (2015) were able to show that this approach worked in tropical forests for at least three tree species and Ferreira et al. (2016) demonstrated this for eight species.

Remote sensing has not yet been used to characterize clove production systems, which can be considered as distinct land use classes in which clove production is taking place. While the creation of land cover maps is one of the most common applications of remote sensing (Foody, 2002), the detection and classification of land use is far more difficult and therefore less common (Lackner and Conway, 2008). The main difficulty in classifying land use is that land use cannot be derived directly from the spectral information of a satellite image, as it often involves higher level reasoning about spatial organization and factors not related to colors and spectra (Aplin, 2003; Lackner and Conway, 2008). To classify land use, a land cover map is usually required first. The challenge then lies in finding additional, meaningful information to classify the land use classes in a second step (e.g., Cihlar and Jansen, 2001; Zhang and Wang, 2003; Lackner and Conway, 2008).

The contribution of this paper can be summarized as follows: 1) individual tree detection by circular Hough transform (CHT) based on very high-resolution (VHR) multi-spectral satellite data, 2) the classification of candidate trees based on a set of visual appearance descriptors encoding spectral information and higher level textural information into cloves/non-cloves classes and the classification and characterization of clove production systems based on descriptors encoding information related to spectral and tree location, and 3) the estimation of clove bud yield in the study area.

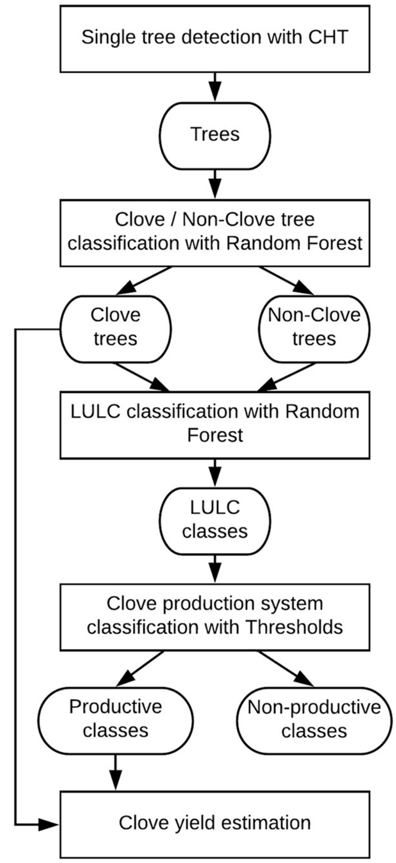

Fig. 1. Flowchart showing the method procedure of this study (described in Section 3).

The proposed method (Fig. 1) and its outputs allow for the creation of a comprehensive map of different clove production systems that allows for the monitoring of future changes in clove production and clove production systems.

2. Study site and data

2.1. Study site

The study site is located in the northeastern part of the Analanjirofo region in Madagascar (center point at −15.379678 Lat, 49.920708 Long). Analanjirofo, literally meaning ‘forest of cloves’, is Madagascar's main clove production region (Levasseur et al., 2012). The study site is approximately 16 × 16 km (25,600 ha) including the surroundings of the villages of Mahavelona and Navana.

Aside from the urban areas and rice fields, which are located along the coast or in valleys, the hillsides mostly contain agroforestry systems, pastures with some individual trees or a few small rice paddies. Continuous dense primary forest is becoming rare and it can be found almost exclusively far from human settlements.

2.2. Clove trees and clove production systems

Clove trees have evergreen leafage of a bright green and are characterized by narrow oblong, circular crowns with diameters of up to

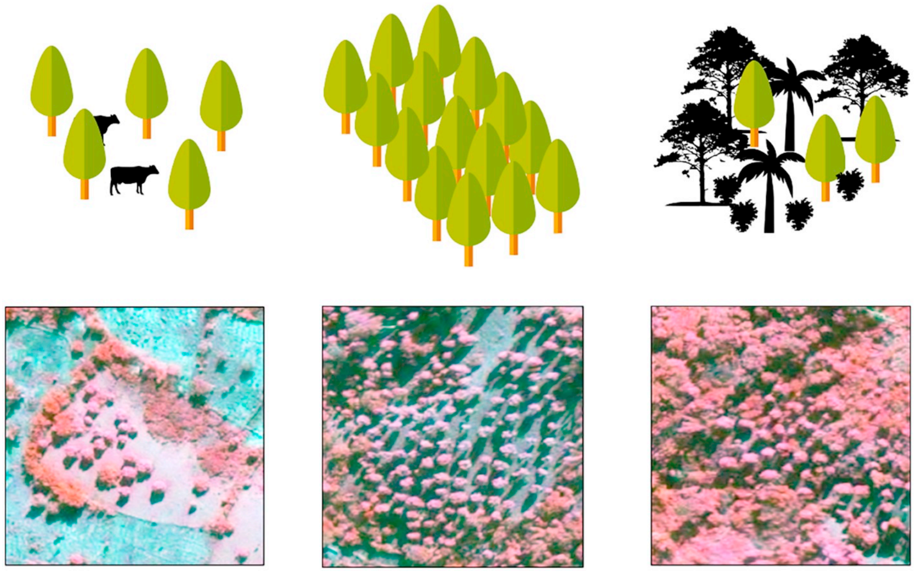

Fig. 2. Schematic and false-color Pléiades satellite imagery (Section 2.3) representation of the three clove production systems. Left: pasture & clove; center: clove plantation; and right: agroforest.

approximately 10 m and tree heights ranging from 12 to 15 m (Lobietti, 2013; Danthu et al., 2014).

The clove tree is mainly cultivated for its flower buds and its eugenol-containing essence extracted mostly from the leaves. Clove yield undergoes a triennial cycle. A year of high yield is generally followed by two mediocre or even poor yield years (Levasseur et al., 2012; Ministère des Affaires étrangères, 2012). On average, balancing age and cycle-related yield fluctuations, a clove tree yields 2–3 kg of dry clove buds per year (Locatelli, 2000, Clove Crop Cultivation Guide n.d., Horticulture Spice Crops n.d.). To produce the eugenol-containing essence, the young leaves are cut. This can be done once every four years and results in approximately 80 kg of leaves per tree. The harvest of clove buds is incompatible with the harvest of leaves (Ministère des Affaires étrangères, 2012).

In line with the current discourse we define the three prevailing clove production systems in Madagascar as follows: *silvo-pastoral systems* (hereafter called 'pasture & clove'), *monoculture-like clove plantations* (here after called 'clove plantations') and *multicrop-multilayer agroforestry systems* (hereafter called 'agroforest') (Fig. 2) (Levasseur et al., 2012; Lobietti, 2013; Danthu et al., 2014).

These three production systems are part of the following five major land use and land cover (LULC) classes that comprise the study area (Table 1).

The detection and classification of the LULC classes in Table 1, however, is not trivial. To separate the clove-producing land use classes (pasture and clove, clove plantation and agroforest) from the remaining non-clove-producing LULC classes present in the study area (Table 1), additional information about the features that enable a finer discrimination is required. The only known feature allowing for this semantic distinction (productive from non-productive LULC classes) is the increased occurrence of clove trees.

To date, the only available information on cloves and clove production systems comes from local fieldwork utilizing interview inquiries carried out in different regions of Madagascar (Locatelli, 2000; Levasseur et al., 2012; Lobietti, 2013). These studies provide information on the density of cloves per hectare, the distance between individual clove trees and clove yield estimates. However, values vary greatly between the different studies, as they were collected in different places in Madagascar. In particular, the number of clove trees per hectare, which is of importance in this context, is rather diverse. For this reason, manually detected reference clove trees were statistically analyzed to find the minimum clove tree density per clove production system in our study area. Based on this analysis, we defined pasture & clove systems as grasslands with at least 9 trees per hectare, clove plantations as plantations with at least 43 clove trees per hectare and agroforests as forested areas with more than 9 clove trees per hectare. LULC classes with fewer clove trees per hectare are classified as non-clove-producing classes.

Table 1
Definitions of the five major LULC classes and the tree production systems present in the study area.

LULC classes	Definition
Grassland	Grasslands are areas of grasses for livestock grazing. In our study area these patches of grassland are often surrounded by bamboo tree hedges and have only a few trees (one or two) in the patch (often a mango or litchi tree). We define *Silvo-pastoral production systems* ('pasture and clove') as grasslands with mainly clove trees in which other trees, such as mango or litchi, can be found sporadically. Clove trees can be either planted in straight lines or scattered over the pasture.
Plantation	Plantations are areas that have been planted to produce food or cash crops. These crops make up approximately 75–100% of the cover (The USGS Land Cover Institute (LCI) n.d.). Only clove plantations are considered in the study area. We define *monoculture-like clove plantations* ('clove plantations') as densely planted clove stands with no other use found on the same plot.
Forest	Forests are characterized by tree cover which, together with woody vegetation, makes up the largest part of the area. Madagascar's forests consist of evergreen species that result in a year-round green canopy (Kägi, 2008). *Multicrop-multilayer agroforestry production systems* ('agroforest') in general are composed of three layers of vegetation. They include clove trees, fruit trees, primary forest trees, and coffee plants (in decreasing occurrence) (Michels et al., 2011).
Sparse vegetation	Areas with little or no "green" vegetation. Includes rice paddies in cases of non-production at the time of the satellite overpass. Additional short periods of bare soils result mainly from shifting cultivation activities.
Urban areas	Areas containing artificial, human-made structures such as buildings or roads.

2.3. Data

Two satellite image strips recorded by the Pléiades 1A satellite on July 9, 2014 were used. Both images were delivered as 'ortho products', which are georeferenced and corrected from acquisition and terrain off-nadir effects (ASTRIUM, 2012). The images have a 2 × 2 m spatial resolution for the RGB and NIR bands and a spatial resolution of 0.5 × 0.5 m for the panchromatic band. Due to the perfect cloud-free conditions, no further pre-processing (such as atmospheric correction or cloud masking) was applied. The Pléiades imaging instrument offers a spectrally wide panchromatic band that also covers a large fraction of the NIR band. For our region, the coefficient of determination (R-squared 0.71) between the panchromatic and NIR bands allows for pan-sharpening of the data to enhance the information content of the image. Because of the importance of the spectral information to later distinguish the clove trees from the surrounding trees, principal component analysis (PCA) pan-sharpening was chosen. Virtually, this method does not introduce spectral distortion and still performs well with respect to the spatial resolution enhancement (Zhang et al., 2014; Pushparaj and Hegde, 2017). All further analyses were either performed on the original panchromatic band or on the processed pan-sharpened multispectral image.

The reference data was acquired manually by an independent expert photo interpreter based on specific structural and optical characteristics (Fig. 2), such as the landscape pattern, tree canopy cover and the composition of clove-trees and non-clove trees. Two types of reference data were collected. On the one hand, reference areas that unambiguously represent the different production systems were identified, considering a stratified distribution of the reference sites over the entire study area. On the other hand, individual clove trees were detected and marked to validate the individual tree detection. To ensure that the correct trees were marked, the expert had some photos of clove trees available for training. This method of visually gathering reference data is regarded as a standard method in forestry (e.g., Hay et al., 2005; Falkowski et al., 2009) and has been widely used in studies with vast and inaccessible study sites that challenge the gathering of a sufficient amount of reliable in situ data (e.g., Ernst et al., 2013; Stibig et al., 2014). Accordingly, 20 square polygons encompassing an area of 1 ha (ha) were distinguished for each of the clove production systems (Fig. 3). Within this total of 60 polygons, all visually detectable clove trees were marked, resulting in a total of 2194 reference clove trees.

Furthermore, for the validation of the five main LULC classes (Table 1), another 20 reference areas of 1 ha were distinguished for each of the LULC classes, such as sparse vegetation and urban areas.

3. Methods

3.1. Individual tree detection and tree crown delineation

Tree crown delineation using optical data, as it is used in this study, is based on the fundamental assumption that the center of a crown is brighter than its edge (Culvenor, 2003). Hence, individual tree detection algorithms traditionally search for either the shadows surrounding an individual tree (e.g., Gougeon, 1999; Leckie et al., 2003) or for the bright crown centers, with the second approach being more commonly employed. The crown centers are found by searching for local radiometric maxima and using them as 'seeds' to grow the crown until a certain stop criterion is reached, such as a global minimum threshold or a minima boundary (Brandtberg and Walter, 1998; Culvenor, 2002; Culvenor, 2003; Wulder et al., 2004; Hirschmugl et al., 2007). Such approaches have the disadvantage of being based on the assumption of every tree having a more or less encircling shadow and a clearly identifiable center. Thus, they are not suited for very dense and complex structures such as tropical forests (Clark et al., 2005). Furthermore, it makes the result dependent on the solar zenith angle, as shade varies depending on the position of the sun (Gougeon, 1999; Culvenor, 2003).

Another widely used individual tree detection approach is to match a three-dimensional synthetic tree crown image model to radiometric values in the image (Pollock, 1996; Culvenor, 2003). Such algorithms mainly try to generalize the shape of the crown based on, for example, the shape of an ellipsoid (Pollock, 1996; Wolf and Heipke, 2007). Although such algorithms are shadow-independent in principle, they have difficulties dealing with varying shapes of tree crowns as is the case in mixed species forests or tropical forests (Culvenor, 2003).

Although the choice of an individual tree detection method depends mainly on the type of forest to be classified and the data available, it is also important to consider the further use of the data. In our case, we must be able to determine the tree species based on the data from the automatic individual tree detection. According to Chubey et al. (2006), more information can be gained from image objects consisting of several pixels relative to individual pixels. Thus, it is not only possible to calculate aggregative statistics regarding the spectral values but also to obtain information about the size, shape or texture of the object (Chubey et al., 2006).

Due to the complex interweaving of different LULC background classes, the general difficulty of classifying trees in tropical rainforests and the fact that two-dimensional image objects facilitate tree species classification, we advocate a completely new approach to individual tree detection. We adopt a clove tree detection method based on two steps. First, we detect all of the candidate trees fitting some empirically defined clove tree model. Then, all of these candidate trees are classified into cloves/non-cloves by applying a machine learning technique, which involves the classification of every possible circle inscribed in the image space by a set of radii.

Taking advantage of the almost perfectly circular crown shape of clove trees, we propose to apply the circular Hough transform (CHT) to detect clove trees (Duda and Hart, 1972; Atherton and Kerbyson, 1999; Rizon et al., 2005). To our knowledge, CHT has not yet been used for automated individual tree detection. However, its use looks promising as it combines all of the abovementioned approaches to detect individual trees: it provides an approximation of the boundary of the trees and center in one pass, by generalizing the tree crown as a circle.

CHT, a common method for circle detection, aims to find circles of a given radius R in images (Atherton and Kerbyson, 1999). CHT is said to be robust to the presence of noise, varying illumination conditions and occlusion (Atherton and Kerbyson, 1999). Moreover, it benefits from

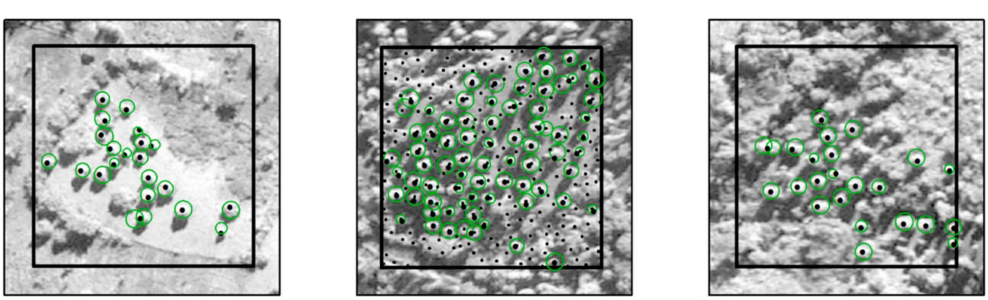

Fig. 3. Examples of 1 ha reference areas (black squares) for each production system, showing the reference clove trees (large black dots) and the radii of the CHT-detected trees (green circles). For display purposes, only the CHT radii are shown that include a reference clove tree for pasture & clove (left) and agroforest (right). The clove plantation example (middle) additionally shows the circle centers (small black dots) of all the CHT-detected circles in this reference area. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the standard Hough transform, which maps a set of feature points from the image space (x-y plane) to a parameter space used to perform inference.

We automatically detected the centers of the individual tree crowns on the original panchromatic image by applying the CHT (The MathWorks Inc., 2012). We used the assumption of bright polarity because the clove trees are brighter than the image background. As most clove trees in the scene do not exceed a diameter of 8 m, the radius range was empirically set to span from 1 m to 4 m. However, by testing other ranges, we found that the detection rate was not sensitive to the radius range. We then used experimental testing to set the other CHT parameters (Huang and Wang, 2006 and Tuia et al., 2010), including the radius of the clove trees, the sensitivity and the edge threshold. The sensitivity was set to the maximum value of 1 to increase the amount of detected circular objects and thus increase the chance of finding as many clove trees as possible. It should be noted that the actual clove tree detection is performed by classifying the set of candidate trees determined by the CHT. Therefore, accepting a high number of false positives is actually beneficial to the overall detection rate. The edge gradient threshold, which determines the edge pixels in the image by setting a gradient threshold, was set to 0.2 on a scale from 0 to 1. Lower edge threshold values lead to more detected circular objects, as objects with both weak and strong edges are detected (The MathWorks Inc., 2012).

Finally, to perform the clove tree classification, we transform every CHT output into a polygon. Each candidate tree is defined by a unique ID, which is associated with center coordinates and a radius. Then, these individual circular objects are used as a basis for feature extraction and clove tree classification.

3.2. Clove tree classification

For both the classification of the clove trees as well as the classification of the clove production systems, we employ a random forest classifier. Random forests (RF) have been shown to provide high accuracies for remote sensing and ecology problems involving supervised classification (e.g., Breiman, 2001; Pal, 2005; Lawrence et al., 2006; Watts and Lawrence, 2008; Dalponte et al., 2012). We prefer RF to support vector machines (SVMs) because of its straightforward interpretation of the hyperparameters (number of trees and depth) compared to SVMs, where several parameters have to be carefully defined (Pal, 2005; Lawrence et al., 2006; Dalponte et al., 2012). Another advantage of RF is that they are less prone to suffer from imbalanced data, differently scaled data or missing values (Pal, 2005). Finally, by training a sufficiently large number of trees, they are robust to overfitting (Breiman, 2001; Lawrence et al., 2006; Rodriguez-Galiano et al., 2012).

The clove detection is defined as a binary classification problem. One class represents the clove trees, while the other one represents all the non-clove trees (Fig. 3). For this reason, we categorized as clove all the candidate trees detected by CHT that contain a clove tree manually identified in the reference dataset. This allows more flexibility by accounting for slightly misaligned tree centers. The remaining candidate trees then belong to the non-clove class.

To mitigate the drawbacks of imbalanced classes, we downsampled the majority class for training (Kubat and Matwin, 1997; Chen et al., 2004). Hence, 1000 samples each of clove and non-clove trees were randomly selected. After the elimination of small tree circles fully circumscribed by larger tree circles, a total of 992 cloves and 997 non-cloves were used for training the RF.

For every candidate tree, we extracted several features describing the objects' spectral and textural properties. In this respect, we decided on the features that have already been applied frequently and successfully in other studies (e.g., Huete et al., 2002, Culvenor, 2003, Ferreira et al. (2016)). We used the mean and standard deviation per channel per crown, skewness and kurtosis, average NDVI (normalized difference vegetation index (Rouse et al., 1973)), average EVI (enhanced vegetation index (Huete et al., 2002)), average SAVI (soil adjusted vegetation index (Huete, 1988)), average VARI (visible atmospherically resistant index (Gitelson et al., 2002)), contrast, correlation, energy and homogeneity within a tree crown (The MathWorks Inc, 2006), 'interest point descriptors' (The MathWorks Inc., 2012) and 'histogram of gradients (HOG)' (Dalal and Triggs, 2005; The MathWorks Inc, 2013). All of these features were calculated for every candidate tree, including for training and validation trees as well as for the approximately 8 million yet-unclassified candidate trees.

For the calculation of contrast, correlation, energy and homogeneity within a tree crown, we used the NIR channel of the pan-sharpened images to calculate these features from the gray-level co-occurrence matrix (GLCM) (The MathWorks Inc, 2006). By calculating the predictor importance (The MathWorks Inc., 2009) we found the standard deviation feature for the NIR channel to be the most descriptive; thus, the NIR channel might generally contain better information to distinguish cloves from non-cloves.

The calculation of the 'interest point descriptors' was performed with the 'extractFeatures' function in MATLAB with which we derived the descriptors from square neighborhoods of different sizes around the trees' center points (The MathWorks Inc., 2012).

After all features were calculated, a random forest classifier, as proposed by Breiman (2001), was applied. To further mitigate the influence of an imbalanced data set, a class-sensitive cost function was applied (Kubat and Matwin, 1997, Chen et al., 2004). The experimentally determined cost applied is $\begin{pmatrix} 0 & 1 \\ 5 & 0 \end{pmatrix}$. This means that cloves trees wrongly classified as non-clove trees are penalized 5 times more than non-clove trees classified as clove trees, mitigating the ambiguous visual appearance (Chen et al., 2004). Note that the 0 values mean that correct classifications are not penalized. This cost matrix resulted in best results for both sensitivity and precision. Although higher restrictions further increased the values of the sensitivity parameter, precision was adversely affected and deteriorated, resulting in an inferior overall result.

After all detected trees were classified, tree centers lying within an experimentally determined distance of 1.5 m were merged (in a process called the non-maxima suppression step). Consequently, multiple detections of one tree from asperities in the tree crown were eliminated. If all tree centers within the distance range were of the same class, their midpoint was calculated to locate the new center and the average radius was assigned. In case one point was classified as clove and the other as non-clove, the clove center was prioritized. This implies that the class, the location and the radius of the clove tree center was retained to avoid losing too many of the clove trees as they are essential for the production system classification.

3.3. Classification of land use/land cover and clove production systems

The classification of clove production systems aims to detect the three clove production systems: pasture & clove, clove plantation, and agroforestry (Section 2.1). As in the clove tree classification step, random forest was used as the classifier.

We used a two-step classification, as in most land use-classification studies (Aplin, 2003; Lackner and Conway, 2008). In the first step, the main land LULC classes, as defined in Table 1, are classified. In the second step, the number of clove trees is used to further distinguish between the main LULC and the clove production systems (Fig. 4).

Although we initially planned to perform the classification of clove production system on areas of 1 ha, it became apparent that this resolution was too coarse, as the farmer's plots were mostly smaller than 1 ha, which caused major class mixture problems. This observation is also confirmed by Lobietti (2013) and local fieldwork performed in 2016 which describes plots to be approximately 0.2 ha in size. To better reflect these reported spatial plot sizes in production classes, we

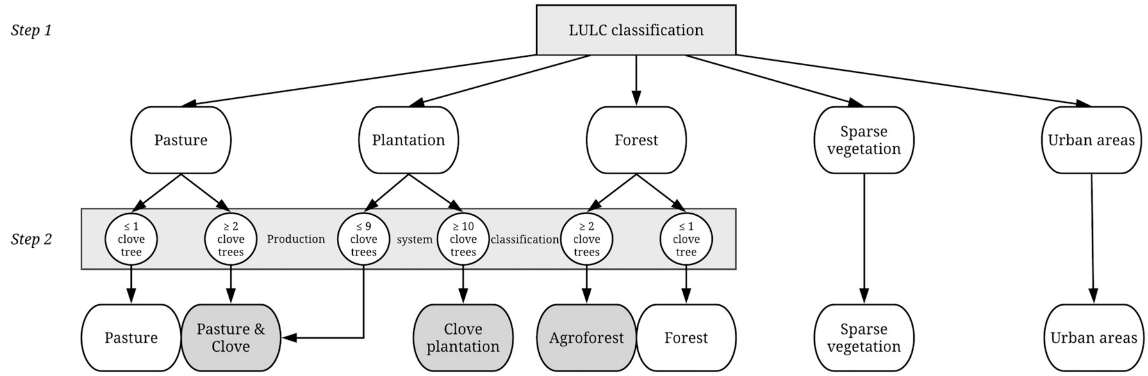

Fig. 4. Two-step classification process to obtain the clove production systems. The first step classifies LULCs with a random forest classifier. The second step classifies the clove production systems based on the presence/absence of a certain amount of CHT-detected clove trees.

subdivided the standard 1 ha plot size to 0.25 ha, allowing us to retain a square grid within the 1 ha plots, similar to the reported plot sizes, and undivided 0.5 m Pléiades pixels.

3.3.1. LULC classification

In the first step, the five LULC classes (grassland, plantation, forest, sparse vegetation and urban areas (Table 1)) were classified based on the extracted features described subsequently.

Using the outcome of the clove tree classification, a cluster and outlier analysis based on Moran's I (ESRI n.d.) was performed on the entire image. Accordingly, spatial clusters of clove trees and non-clove trees were determined. Areas having only few clusters of trees were assumed to be very likely grasslands, bare soil or urban areas. For each grid cell of 0.25 ha, the calculated cluster specifications were stored. Furthermore, the distance between each tree and its nearest neighbor tree was calculated. Subsequently, a statistical analysis of these distance measures was performed per 0.25 ha region. The calculated statistical values were sum, mean, minimum, maximum, range and standard deviation.

In addition to the spatial object-based information gathered from the detected trees, the spectral information was considered as well. For all pan-sharpened pixels within each 0.25 ha region, the sum, mean, median, minimum, maximum, minority, majority, range, standard deviation and variety statistics were calculated based on their respective intensity.

These features were used as inputs to the RF classifier. Due to the very balanced training set, no class-weighted cost function was used at this time.

3.3.2. Clove production system classification

In this final classification step, we aim to separate the clove production systems from the main LULC classes. Because the grassland and forest classes are almost identical in terms of spectral reflectance to the clove production systems classes (Aplin, 2003), the only difference is the presence or absence of clove trees. The respective thresholds for the minimum amount of clove trees per production system were calculated based on the reference production system area of 1 ha (Section 2.2). This resulted in a minimum of 2 clove trees per 0.25 ha for pasture & clove and agroforest areas and 10 clove trees per 0.25 ha for clove plantation areas.

These thresholds were applied to the production system classification (Fig. 4). The LULC class grassland is classified as grassland when there are only zero to one clove trees present. Grasslands having at least two clove trees are categorized as productive pastures with respect to clove production. The same threshold is applied to the forest LULC class, which is divided into primary forest and areas used for agroforestry. Due to the spectral similarity of grasslands and plantations, this LULC class was also re-evaluated using the amount of clove trees. Plantations having 9 or less clove trees are reclassified as pasture and clove, while plantations having 10 or more clove trees are classified as clove plantations. By knowing which areas of the study site are used to produce cloves, together with the number of clove trees in these areas, estimates can be made to quantify potential clove production rates.

3.4. Clove bud yield estimations

One of the main objectives of calculating the average clove bud yield, as well as the clove density and the distance between clove trees per production system, is to be able to supplement data from the literature with our data. We consider this to be important, as there is currently little information on cloves and their production in Madagascar, and therefore each additional study contributes to a better understanding of this crop and its local cultivation. Estimating clove yields in general is a difficult task, as they undergo complex triennial fluctuations and are also dependent on the age of the clove tree. Furthermore, there is no official data about clove yields in Madagascar. Some sources estimate that a clove tree yields on average 2–3 kg of dry clove buds per year when age and cycle-related yield fluctuations are balanced out (Locatelli, 2000, Clove Crop Cultivation Guide n.d., Horticulture Spice Crops n.d.). Other studies estimate a considerably higher yield per tree (up to 25 kg/tree), while others estimate it to be lower (approximately 1 kg/tree) (Table 2). Due to these uncertainties, we base our calculations on the mean value of 3 kg per tree.

For the yield calculation, we multiplied the amount of detected clove trees with this average yield value and calculated the average yield per production system as well as the total yield of clove buds in the entire study area. Other clove products, such as the leaves from the clove trees or the essential oil, were not taken into account as no or only little reliable information exists about yield quantities.

4. Results

4.1. Individual tree detection and tree crown delineation

The single tree detection based on the CHT algorithm resulted in a detection rate of 97.9% of the clove reference trees; that is, 2147 of the 2194 reference clove trees were located within the radius of the CHT detected tree polygons (Fig. 3). The exact position of the reference tree within the CHT crown radius, however, was not taken into consideration.

4.2. Clove tree classification

The clove tree classification based on RF resulted in an overall accuracy (OA) of 90.8%. This value for accuracy, however, is not representative, as the validation set with the remaining trees is still

Table 2
Summary of data found in the literature about clove production systems in Madagascar supplemented by the information obtained in the present study.

	Pasture & clove				Clove plantation				Agroforest			
	Density [trees/ha]	Distance [m]	Dry yield [kg/tree]	Dry yield [kg/ha]	Density [trees/ha]	Distance [m]	Dry yield [kg/tree]	Dry yield [kg/ha]	Density [trees/ha]	Distance [m]	Dry yield [kg/tree]	Dry yield [kg/ha]
Data from own field work (2016)	–	7–10 5.7–7.4	4	–	–	5–7 6.4	–	–	–	7.1	5	–
Levasseur et al., 2012[*]	354 50 Mean: 202	–	0.47[**] 0.048[**] Mean: 0.26[**]	167 2.4 Mean: 84.7	96	–	2.4[**]	230	337 156 Mean: 246.5	–	1.5[**] 0.72[**] Mean: 1.11[**]	509 113 Mean: 311
Lobietti, 2013	180	–	–	–	239	–	–	–	195	–	–	–
Locatelli, 2000	–	–	–	–	150 Range: 30–300	8	3 Range: 3–25	–	–	–	–	–
Ministère des Affaires étrangères, 2012	–	–	–	–	–	4–5	2–5	450	–	–	–	–
Present study	18	11	3[***]	53	71	6.5	3[***]	213	21	10	3[***]	63

[*] Values from Levasseur et al., 2012 are sampled at two different sites; mean was calculated for this study.
[**] Values calculated for this study by dividing the reported yields/ha by the number of trees per hectare.
[***] Estimate based on a literature survey.

Table 3
Confusion matrix of the clove tree classification based on RF.

		Reference		
		Clove	Non-clove	User accuracy
Prediction	Clove	1946	1339	59.2%
	Non-Clove	805	19,190	95.9%
	Producer's Accuracy	70.7%	93.5%	

extremely imbalanced. Hence, we calculated a confusion matrix with the classification results averaged from 100 iterations (Table 3).

From a total of 2751 validation clove trees, on average 1946 were correctly classified as clove trees over 100 iterations. Slightly less than a third were incorrectly classified as non-clove tree. The vast majority of 20,529 circular objects were used as the non-clove tree validation set. Of these, 19,190 were correctly classified as being not a clove tree. 1339 were classified as clove trees although they actually were a non-clove tree. These values result in a 70.7% producer's accuracy (PA) for clove trees and a 93.5% PA for non-clove trees averaged over 100 iterations. The user accuracy (UA) is 59.2% for clove trees and 95.9% for non-clove trees. Deduced from the confusion matrix, the classification has a mean accuracy of 84.2% (Fig. 5).

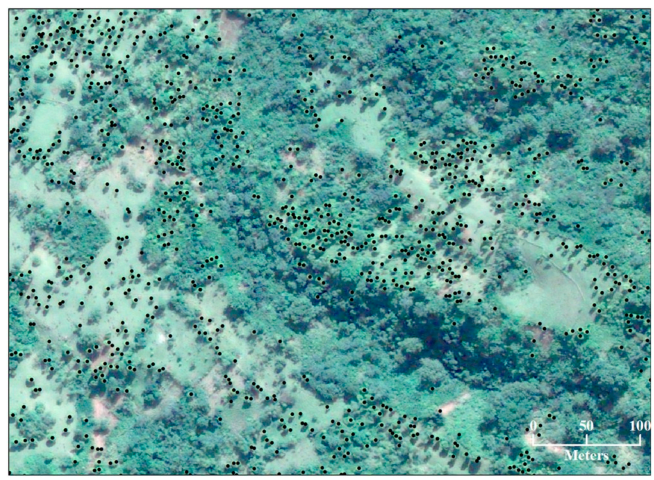

Fig. 5. Excerpt of the study site showing the automatically detected and classified clove trees (black dots).

4.3. Classification of land use land cover and clove production systems

To evaluate the production system classification, a two-step validation system corresponding to the two classification steps (Section 3.3) has been applied.

4.3.1. Land use land cover classification

To validate the first classification step (the LULC classification), the reference LULC classes were split into a training and a validation set. Each set contained 40 training/validation plots for each LULC class. To understand the contribution of the tree-related information (cluster analysis and distance), we present the results from the classification solely based on spectral reflectance and from the classification using both the spectral and tree-related information (Table 4). Similar to the clove tree identification, we performed 100 iterations of the RF classifier.

As all classes are here perfectly balanced, the overall accuracy is a suitable measure of the reliability of the classification. The OA using both spectral information and tree related information is 87.5%, 12% more than when using solely the spectral information (75.5%). The same applies to the user and producer accuracies for each class. For the two approaches, the best UAs are achieved for the sparse vegetation and urban area classes, since they have very distinct spectral behavior. As expected, the use of combined information significantly improves the classification results for the plantation (UA = 77.5%, PA = 70.5% versus UA = 35% and PA = 48.3%) and grassland (UA = 75%, PA = 90.9% versus UA = 67.5% and PA = 56.3%), since they have similar spectral properties in the considered wavebands. Considering these results, the classification based solely on the spectral information will not be used further in this study.

These results show the added value of the tree-related information determined with the circular Hough Transform as well as the tree classification. It also indicates the importance of applying this additional information in a second classification step to further refine the classification output and to distinguish productive and nonproductive LULC classes.

4.3.2. Clove production system classification

The classification of the clove production systems is shown in Fig. 6. To validate the production system classification, equalized stratified

Table 4
Confusion matrices of the LULC classification. Left: using spectral features only (OA = 75.5%); right: using both spectral and tree related information features (OA = 87.5%). The results are averaged over 100 iterations.

	Spectral features only						Spectral features & clove-related features					
Reference/ Prediction	Grassland	Plantation	Forest	Sparse vegetation	Urban	User's Accuracy	Grassland	Plantation	Forest	Sparse vegetation	Urban	User's Accuracy
Grassland	27	9	0	4	0	67.5%	30	8	0	2	0	75.0%
Plantation	19	14	6	1	0	35.0%	3	31	6	0	0	77.5%
Forest	0	5	35	0	0	87.5%	0	4	36	0	0	90.0%
Sparse vegetation	2	1	0	35	2	87.5%	0	1	0	38	1	95.0%
Urban	0	0	0	0	40	100.0%	0	0	0	0	40	100.0%
Producer's accuracy	56.3%	48.3%	85.4%	87.5%	95.2%		90.9%	70.5%	85.7%	95.0%	97.6%	

random sampling was applied over the entire study area to get 20 samples per production system. These samples were then classified by an expert with a similar approach as described in Section 2.3. Subsequently, the expert-based classification was compared with the classification outputs of the production system classification. The outputs from this validation are displayed in Table 5.

The OA of the production system classification is 77.9%. The averaged PA over all classes is 80.5% (ranging from 64% to 100%) and the averaged UA over all classes is 77.9% (ranging from 65% to 95%). The lowest accuracies are obtained for cloves (UA = 65% for clove plantation and agroforest, and PA = 68% for pasture and clove and 68.4% for agroforest). The class accuracies are more heterogeneous than in the LULC classification, as the problem is more complex.

4.4. Clove bud yield estimations and uncertainties

By considering a per-tree yield of 3 kg (reference), we computed a total yield of approximately 465 tons of cloves for the entire study area. In addition, we calculated the average yield per system of production, as well as the average clove density and the average distance between clove trees per production system (Table 6).

According to our calculations, pasture and clove systems produce an average yield of approximately 53 kg/ha. A similar amount is achieved in agroforests. Clove plantations, on the other hand, produce considerably more dry clove buds due to the higher number of trees. Here, the yield is approximately 213 kg/ha. The average clove tree density and distance for both pasture and cloves and agroforest are in the same range of approximately 20 trees/ha and 10 m, respectively. The average distance of approximately 6.5 m between clove trees on plantations is also confirmed by Maistre (1964) and Danthu et al. (2014).

Our yield calculations are based on the assumption that a clove tree produces an average of 3 kg of dry clove buds over the years. The values from the literature, however, sometimes deviate strongly from this average. This inevitably leads to a high uncertainty about the yield estimation of cloves. Assuming a minimum of 1 kg and a maximum of 25 kg/ha, as found in the literature, leads to the following considerable yield ranges: pasture and clove systems range from 17.5 kg/ha to 437.5 kg/ha, plantations range from 71 kg/ha to 1775 kg/ha, and agroforest systems from 21 kg/ha to 525 kg/ha.

Calculated over the entire area, already small differences result in highly different estimations of yield. Assuming for example an average yield of only 2 kg, the total amount of dry clove buds produced would be (linearly) reduced to 383 tons for the entire study area. Assuming 5 kg/tree, however, the yield would increase to 959 tons. Since not only the choice of yield per tree but also other factors, such as the farmers' decision to harvest cloves or leaves, influence the final yield, we have additionally calculated the number of productive trees. This is the number of CHT detected clove trees located in an area classified as a clove production system (Table 7).

5. Discussion

Before feeding the satellite data to our processing chain, pre-processing of the data was evaluated and performed. In this study, we decided not to apply an atmospheric correction as the study covers only a single point in time and it was shown by Lin et al. (2015) that

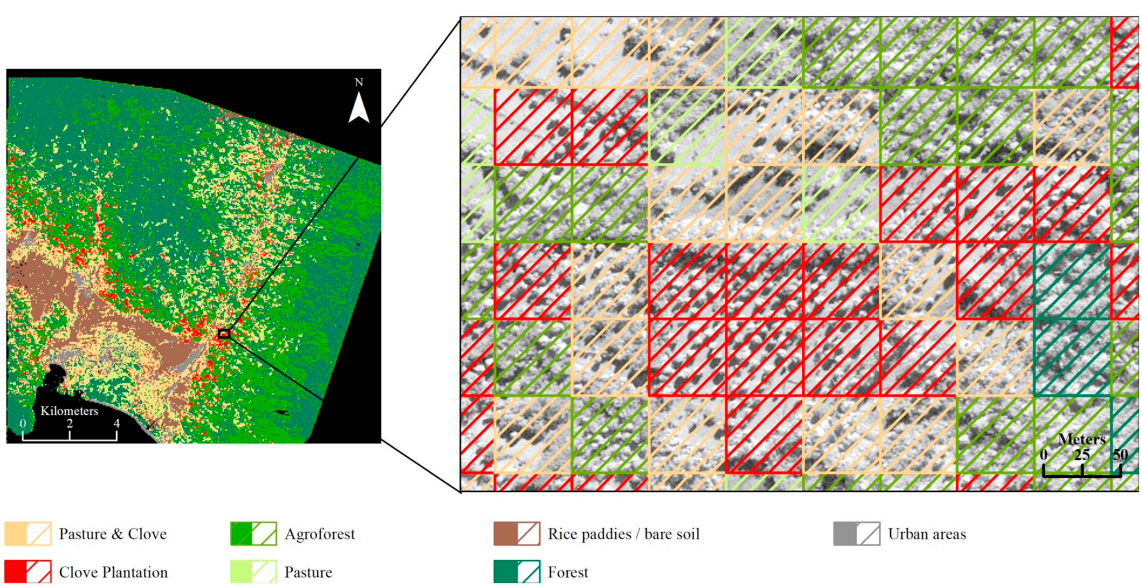

Fig. 6. The classification of clove production systems for the whole study area (left) and an excerpt (right).

Table 5
Confusion matrix of the production system classification.

Reference/Prediction	Pasture and clove	Clove plantation	Agroforest	Grassland	Forest	Sparse vegetation	Urban	User's accuracy
Pasture and clove	17	1	1	0	0	1	0	85.0%
Clove plantation	4	13	3	0	0	0	0	65.0%
Agroforest	0	0	13	0	7	0	0	65.0%
Grassland	0	0	0	17	1	2	0	85.0%
Forest	2	0	2	0	16	0	0	80.0%
Sparse vegetation	0	0	0	1	0	19	0	95.0%
Urban	2	0	0	0	1	3	14	70.0%
Producer's accuracy	68.0%	92.9%	68.4%	94.4%	64.0%	76.0%	100.0%	

Table 6
Average clove tree density and average distance between clove trees per 1 ha production system plot.

	Pasture and clove	Plantation	Agroforestry
Average density [trees/ha]	17.5	70.9	21.0
Average distance [m]	10.8	6.5	10.2
Average yield [kg/ha]	53	213	63

Table 7
Number of clove trees in clove production areas in the entire study area.

	Pasture and clove	Plantation	Agroforestry	Total
Number of clove trees	4236	40,833	108,545	191,743

atmospheric correction has a negligible influence on the classification outcomes in VHR satellite images. However, the training data set must be updated each time when applying it to another image dataset, as changing atmospheric and other conditions (e.g., seasonality) will influence the training.

The multi-spectral bands have been pan-sharpened to allow use of the image content at the highest possible spatial resolution. Although the coefficient of determination between the panchromatic and the NIR band is considerable, it is still not very high. Consequently, we expect a spectral distortion in the pan-sharpened NIR band, which reduces the spectral diversity. However, the benefit of a higher spatial resolution prevailed over the remaining spectral distortion in the pre-processed data.

5.1. Individual tree detection and tree crown delineation

From the results obtained by applying CHT to detect clove trees, we infer that CHT is a promising algorithm for automated single tree detection. The detection rate achieved with the CHT approach is in the upper range of common detection rates ranging from approximately 60% to over 90% (e.g., Pouliot et al., 2002; Srestasathiern and Rakwatin, 2014; dos Santos et al., 2017). The detection is of similar quality for the different production systems (Fig. 3). This approach also excelled with respect to its easy applicability. While other approaches require several steps to detect tree crown centers and crown boundaries, CHT automatically provides these outputs in a single step. CHT is especially well suited when the tree position is of major interest to count trees or deduce tree densities. Approximations about crown sizes are also feasible. However, reducing tree crowns to circular shapes will not be suitable for all tree species and will not give exact tree crown delineations that might be required for some applications. Further post-processing on CHT detections could be developed to tackle such issues.

Although the CHT detection rate and crown delineation outputs are promising, we also identified some weaknesses of this method. As the algorithm first identifies gradients in the image, circular objects other than clove tress are also identified. Urban areas, bare soil and grasslands showing bright reflection spots are specifically affected. Therefore, a classification step discriminating classes of interest plays a crucial role. The potential solution of applying a NDVI mask to mitigate this challenge (at least in the urban areas) was discarded due to the extensive shadow areas in the tropical forest that would have been masked out as well. Another solution to mitigate the hypersensitivity to circular objects is to decrease the sensitivity parameter of the algorithm and increase the edge threshold parameter. Both adjustments will result in fewer detected circles. We did not apply these adjustments as it was our primary goal to detect as many reference clove trees as possible. Another potential solution to reduce the number of detected circles might be to apply a filter in advance of CHT to eliminate weak gradients as they might occur on pastures.

In the present study, CHT detected too many circles due to the site-specific presence of various land covers instead of just forest. We suppose that scenes containing exclusively trees and especially scenes from homogeneous forest patches (as are found in coniferous forests, for example) would perform better.

Hence, one has to be aware that CHT for single tree detection can be used almost only in combination with a subsequent classification if the study area consists of different land cover types. This is necessary to obtain only trees or a specific tree species.

5.2. Clove tree classification

Random forest-based clove tree classification resulted in outcomes with a PA of almost 71% and a UA of almost 60%. Compared to the values of Baldeck et al. (2015), the classification results in this present study are lower. Considering the different preconditions of the studies, these values are evaluated as acceptable and very promising. In our case, the classification was complicated by various factors. Precious information about tree height that was available in Baldeck's study was not available here. Additionally, it was not possible to take advantage of any blossoms that would have clearly distinguished the tree species from others as was possible for Baldeck et al. (2015). Furthermore, only visually acquired references were available as fieldwork in such a vast and remote area was not practical. Although generated by an expert, errors might exist in the reference data. As the principle for the reference collection was to only mark trees as references of we were certain it was a clove tree, omissions are very likely. This might explain a small part of the rather high error of omission concerning clove trees.

The major challenge that reduced the classification quality was most likely the approximated tree crown delineation. Although CHT circles do approximately represent the tree crown, the delineation is difficult and thus spectral signature impurities might occur. There are two main kinds of imprecise delineations. One is that the detected circle is too small. This occurred mainly for very large non-clove trees, such as mango trees, as they exceed the predefined radius of the CHT. This leads to only the rather bright upper part of the tree crown being captured. Hence, the reflection of this tree object was brighter and of a lighter green color, causing the algorithm to misclassify it as a clove tree. This partly explains the rather high number of false positives. The other challenge is that the detected circle is too large. This mainly occurs with small trees with shadowing effects. As the detected circle is larger than the actual tree, the shadow is figured into the calculation of the spectral signature as well. Hence, the spectral signature appears darker and the tree is classified as non-clove. This explains part of the false negative classification results. However, as young and thus small clove trees in general produce only a very small amount of clove buds until they reach an age of 15 to 20 years (Levasseur et al., 2012, Lobietti, 2013, Clove Crop Cultivation Guide n.d.), the effects of excluding these trees in terms of yield calculation are considered to be negligible.

Another challenge is the abovementioned detection of circular objects that are not trees. As the training and validation sets were in vegetation-only areas, mainly the detected circles in bright pastures are problematic. The bright spots on the pastures have a very similar spectral signature to the top of clove trees. Therefore, circles located on pastures were often misclassified as clove trees, resulting in additional false positives.

The predictor importance (The MathWorks Inc., 2009) for the tree classification showed a rather low importance of approximately 0.3 for most features (on a scale from 0 to 1). We suppose this low feature importance results from the high similarity of cloves and the surrounding vegetation, resulting in similar features that are not particularly meaningful for the differentiation. In our case, the features with the highest importance are the standard deviation of the spectral reflections in the bands blue, green and NIR as well as the skewness of the NIR channel per tree crown. Furthermore, some of the interest point descriptors also showed high importance, underlining the important role of texture. In our data the most important feature, with a feature importance of 0.65, was the standard deviation of the crowns' spectral reflectance in the NIR channel. The importance of the NIR channel is also apparent when looking at the false-color image where the clove trees have a slightly different hue compared to the surrounding vegetation (Fig. 2).

It turns out that clove tree classification correctly eliminated most of the circular objects that were not trees (e.g., bright spots on pastures/bare soil) and provided a reliable overall classification of the separation of clove trees from other trees. Considering the varying terrain and illumination effects, the classification output is promising to use as input for the clove production system classification.

5.3. Classification of LULC and clove production systems

The LULC classification performed well and produced a good overall accuracy. The combination of spectral information with specific single tree-related information such as tree class (clove/non-clove) or tree location resulted in a 12% better classification result compared to utilizing spectral information only.

When looking at the feature importance, spectral data naturally show very high importance with an average feature importance of 0.7 on a scale from 0 to 1. The improvement of the combined classification very likely results from the maximum distance between trees per plot feature and the information about HL-outliers (an outlier featuring a high (H) value which is surrounded by features having a low (L) value). Their feature importance is 0.7 and 0.71, respectively. This confirms that the main land cover classes, such as urban areas, bare soil or forest, are classifiable with common and well-known spectral approaches. However, as soon as classes are more alike and show spectral overlap, further information is required to improve the classification. Even more information is required to distinguish the specific land use classes (pasture and clove, clove plantation and agroforest) from the non-productive LULC classes.

The production system classification based on clove thresholds is of high quality, as seen in Table 5. The decrease in OA compared to the LULC classification results from the training and validation being no longer based on our homogeneous and ideally class-representing references, but on the very heterogeneous grid cells laid over the entire study area. Introducing a grid over the entire study site resulted in many grid cells that contained a mixture of classes, such as a plantation surrounded by agroforest. While this is induced by the local circumstances of heterogeneous small-scale farming, applying an object-based approach (e.g., Hay et al., 2005; Mallinis et al., 2008) might have mitigated this effect at the cost of more parameters to optimize. For our purpose, the grid-based classification is very suitable. Successfully applying a random forest classifier requires that the features of the data are equal in scale to avoid scale dependency issues. We explicitly enforced scale invariance by using a regular grid with cells of the same size and shape for both the reference and classification datasets. This regular grid was mandatory, because we used thresholds computed using the pre-defined spatial scale. In addition, this is in agreement with Tuominen and Haapanen (2011), who showed that the grid cell approach is still better suited for forest inventories than segmentation, as they achieve better accuracies despite the theoretical advantages of segments. Furthermore, having the same cell size and shape also allows for the identification of specific structures or patterns in the distribution of the clove trees within the grid cell. This also facilitated the calculations of the clove tree densities and the amount of clove yield per hectare. Going more into detail on the production system classification output, we observe that some class accuracies improve inversely to others. This is specifically the case for the user accuracy obtained for urban areas. The main source of error regarding this class was the misclassification of sand (along the beach) and highly reflective bare soils as urban areas. This misclassification, however, already occurred in the first classification step. When the LULC classes were classified, none of the references encompassed such a region (e.g., sand), as only ideal representations of a class were chosen as references. Therefore, this misclassification was not noticed in the beginning as the validation of the LULC classification was based on the ideal references and not randomly sampled grid cells.

The three production systems were quite reliably classified. However, clove plantation and agroforest only achieved a UA of 65%. This is mainly due to the setting of the threshold when distinguishing these two production systems. Setting thresholds to separate classes is always problematic to a certain degree as the model is strict. This was observed in clove plantations. Some plots were classified as plantations although they were pasture and clove systems. Two different critical reasons were identified: (a) more plantations would have been (correctly) classified as pasture and cloves by setting a lower threshold for the plantation to pasture & clove reclassification, and (b) setting a threshold for the reverse reclassification pasture and clove to plantation might have been necessary.

In the agroforest class, the threshold challenge is similar. For example, the rather low threshold of 2 trees/0.25 ha is also reached by forest regions that, due to their location, are most likely not used for agroforestry. To counteract this problem, further information is necessary. If an additional parameter such as the distance from settlements was also included, plots that are far away from settlements would not have been reclassified.

Another reason for the rather low values of PA and UA for the agroforest class could also have originated from the agroforest class as such. Agroforest is not specifically defined. Rather, it is a plot where various plants are cultivated based on the farmer's personal needs and depending on the plots location. Hence, agroforestry plots cannot be standardized and thus they are more challenging to classify than other classes.

Overall, we can conclude that applying a two-step classification verifiably improves the LULC classification. However, at the end of the entire classification procedure from clove tree delineation to production system classification, this approach can suffer from error propagation. We tried to mitigate this effect in the LULC classification by reducing the grid cell size from 1 ha to 0.25 ha to avoid mixed cells. However, the use of a threshold on the number of clove trees to separate the production systems makes the LULC classification sensitive to potential misclassifications of clove/non-clove trees. While we cannot quantify this influence, it is still something one has to keep in mind.

5.4. Clove bud yield estimations

The calculated yields are also influenced by the determination of values and the application of thresholds. The yield value of 3 kg/tree, which is indicated often in the literature, is a choice that has far-reaching consequences. Although this value can be regarded as relatively reliable, yields for the study area may vary by several hundred tons depending on the value used for the calculation.

The thresholds set in the production system classification also lead to further uncertainties in the yield estimate. This can be seen in the classification of agroforest. Due to the low thresholds for agroforest systems (Section 5.3), a large forest area is classified as agroforest (Fig. 6). However, the actual number of agroforest systems in the study site is likely to be lower, as many of these classified agroforest areas are too far away from settlements to be used for clove production purposes. Consequently, the overall yield generated in agroforest systems in this study site will probably be lower than calculated. The average yield generated on a single agroforest system parcel, on the other hand, is likely to be slightly higher than calculated. This is because agroforest parcels close to villages often include 4–7 clove trees, while most of the classified agroforest parcels now have only 2–3 clove trees per 0.25 ha on average. Although the trees near villages, which have not been taken into account in the yield calculation because they grow on non-producing areas based on our classification, might provide a slight compensation for the overestimation of the yield generated by agroforest systems, it might not be able to cancel it out completely.

Due to the absence of ground validation for yields, it was not possible to evaluate the accuracy of our calculations. Compared to existing studies, we found considerably lower yield values per production system (Table 2). This is probably due to fact that the clove tree density was many times higher than in our study area. Further information must thus be taken into account for local variability in yield estimates.

The only other available information is provided by FAOSTAT (n.d.). Unfortunately, these data are incomplete and show a strong variation of yields for the most recent available period (2012–2016). The minimum estimate of the annual dried clove bud production is 15,047 tons (2012) while the maximum amount is 21,864 tons (2015). This large variation is also visible in the export data, with 11,697 tons in 2013 and 20,896 tons in 2016. The same variation applies to harvested area (51,943 ha in 2012 and 70,625 ha in 2015). According to our calculations, 575 t of the total amount of dried clove buds would be produced in our study area. This would be between 2.6% and 3.8% of the total clove production in Madagascar. Considering the size of our study site, which is located in the main clove production area of Madagascar, this seems to be a reasonable percentage. To check if the yield percentage coincides with the percentage share of the production area, we approximated the total productive area in our study site. Adding up the grid cells classified as productive areas would in our case result in an overestimation of the production area due to the overestimation of agroforest production systems. Therefore, we calculated the average area used by a clove tree by taking the average distance to the next clove tree and multiplied it with the total amount of clove trees in our study area (Table 7). This resulted in a total productive area of approximately 1250 ha. Compared to FAOSTAT's production area estimates for the whole area of Madagascar this gives a percentage share between 1.8% and 2.4%. This percentage share for the productive area approximately coincides with the above calculated percentage share of the total yield. Although our results coincide rather well with the information from FAOSTAT, there large uncertainties still remain about their correctness. It was, for example, impossible to decide whether a tree was used for its clove buds or for its leaves that are harvested for essential oil production. Since the latter is incompatible with clove bud harvesting (Danthu et al., 2014), it must be assumed that only a certain fraction of the detected clove trees in the production systems are actually used for the production of clove buds. In situ or local statistical data would be required to calibrate our results.

6. Conclusion

In this study, we combined different state-of-the-art remote sensing data and methods and developed a new method to detect and classify clove trees into the three prevalent clove production systems in Madagascar. We have shown that circular Hough transform (CHT) is a promising and simple-to-use method for automated single clove tree detection in a tropical forest. This method is especially effective when the location of a tree and only an approximate delineation of the tree crown are required. A high detection rate of 97.9% of clove reference trees was achieved.

The outputs from CHT were used to implement a clove tree classification based on a random forest classifier. The NIR band was of prime importance to separate clove trees from other species. The tree classification result was in turn used to successfully classify the three clove production systems: pasture & clove, clove plantation, and agroforest. Combining spectral data with tree-related properties for the production system classification resulted in an overall accuracy of 77.9%. Considering that every processing step introduces uncertainties propagated from the preceding steps, the results are very promising.

Based on the classified production systems, we estimated that the clove bud yield in the study site ranges from approximately 53 kg/ha in pasture and cloves to 213 kg/ha in plantations (63 kg/ha in agroforests) when considering a dry clove bud yield of 3 kg/tree. However, in situ reference yield data ranging from 1 to 25 kg/tree leads to a high uncertainty in our yield estimates. Therefore, we strongly encourage further research, especially in the in situ data acquisition of crop yields and in the fraction of trees used for the clove bud production to better calibrate possible remote sensing-based estimates.

For the first time, we show that clove trees and clove production systems are classifiable on a large scale based on remote sensing data. Generating information using automated methods and providing quantitative results from remote sensing data could offer new insights into agro-statistics in hard-to-reach areas without any well-founded public databases. Based on such information, governmental programs could also benefit, such as those fostering sustainable smallholder agroforestry and agencies determining the most effective employment of development aid resources.

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References

Aksoy, S., Yalniz, I.Z., Tasdemir, K., 2012. Automatic detection and segmentation of orchards using very high resolution imagery. IEEE Trans. Geosci. Remote Sens. 50 (8), 3117–3131.
Aly, M., 2005. Survey on multiclass classification methods. Neural Netw. 19, 1–9.
Aplin, P., 2003. Determining land-use information from land cover through an object-oriented classification of IKONOS imagery. In: Mesev, V. (Ed.), Remotely-Sensed Cities. Taylor & Francis, London, U.K., pp. 23–45.
Asner, G.P., Martin, R.E., Anderson, C.B., Knapp, D.E., 2015. Quantifying forest canopy traits: imaging spectroscopy versus field survey. Remote Sens. Environ. 158, 15–27.
ASTRIUM, 2012. Pléiades Imagery User Guide. 2. pp. 118.
Atherton, T.J., Kerbyson, D.J., 1999. Size invariant circle detection. Image Vis. Comput. 17 (11), 795–803.
Azzari, G., Jain, M., Lobell, D.B., 2017. Towards fine resolution global maps of crop yields: testing multiple methods and satellites in three countries. Remote Sens. Environ. 202, 129–141.
Baldeck, C.A., Asner, G.P., Martin, R.E., Anderson, C.B., Knapp, D.E., Kellner, J.R., Wright, S.J., 2015. Operational tree species mapping in a diverse tropical forest with airborne imaging spectroscopy. PLoS One 10 (7), e0118403.

Battude, M., Al Bitar, A., Morin, D., Cros, J., Huc, M., Marais Sicre, C., Le Dantec, V., Demarez, V., 2016. Estimating maize biomass and yield over large areas using high spatial and temporal resolution Sentinel-2 like remote sensing data. Remote Sens. Environ. 184, 668–681.
Bowler, I.R., 2014. The Geography of Agriculture in Developed Market Economies. Routledge.
Brandtberg, T., Walter, F., 1998. Automated delineation of individual tree crowns in high spatial resolution aerial images by multiple-scale analysis. Mach. Vis. Appl. 11 (2), 64–73.
Breiman, L., 2001. Random forests. Mach. Learn. 45 (1), 5–32.
Chen, C., Liaw, A., Breiman, L., 2004. Using Random Forest to Learn Imbalanced Data. 110. Univ. California, Berkeley, pp. 1–12.
Chubey, M.S., Franklin, S.E., Wulder, M.A., 2006. Object-based analysis of Ikonos-2 imagery for extraction of forest inventory parameters. Photogramm. Eng. Remote. Sens. 72 (4), 383–394.
Cihlar, J., Jansen, L.J.M., 2001. From land cover to land use: a methodology for efficient land use mapping over large areas. Prof. Geogr. 53 (2), 275–289.
Clark, M.L., Roberts, D.A., Clark, D.B., 2005. Hyperspectral discrimination of tropical rain forest tree species at leaf to crown scales. Remote Sens. Environ. 96 (3), 375–398.
Clove Crop Cultivation Guide, n.d. URL https://www.indiaagronet.com/horticulture/CONTENTS/clove.htm (accessed on 11.8.17).
Culvenor, D.S., 2002. TIDA: an algorithm for the delineation of tree crowns in high spatial resolution remotely sensed imagery. Comput. Geosci. 28 (1), 33–44.
Culvenor, D.S., 2003. Extracting individual tree information. In: Wulder, M.A., Franklin, S.E. (Eds.), Remote Sensing of Forest Environments: Concepts and Case Studies. Kluwer Academic Publishers, pp. 255–277.
Dalal, N., Triggs, B., 2005. Histograms of oriented gradients for human detection. In: Proc. - 2005 IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognition, CVPR 2005 I, pp. 886–893.
Daliakopoulos, I.N., Grillakis, E.G., Koutroulis, A.G., Tsanis, I.K., 2009. Tree crown detection on multispectral VHR satellite imagery. Photogramm. Eng. Remote. Sens. 75 (10), 1201–1211.
Dalponte, M., Bruzzone, L., Gianelle, D., 2012. Tree species classification in the Southern Alps based on the fusion of very high geometrical resolution multispectral/hyperspectral images and LiDAR data. Remote Sens. Environ. 123, 258–270.
Danthu, P., Penot, E., Ranoarisoa, K.M., Rakotondravelo, J.C., Michel, I., Tiollier, M., Michels, T., Normand, F., Razafimamonjison, G., Fawbush, F., Jahiel, M., 2014. The clove tree of Madagascar: a success story with an unpredictable future. Bois Forêts des Trop. 320 (2), 83–96.
dos Santos, A.M., Mitja, D., Delaître, E., Demagistri, L., de Souza Miranda, I., Libourel, T., Petit, M., 2017. Estimating babassu palm density using automatic palm tree detection with very high spatial resolution satellite images. J. Environ. Manag. 193, 40–51.
Duda, R.O., Hart, P.E., 1972. Use of the Hough transformation to detect lines and curves in pictures. Commun. ACM 15 (1), 11–15.
Ernst, C., Mayaux, P., Verhegghen, A., Bodart, C., Musampa, C., Defourny, P., 2013. National forest cover change in Congo Basin: deforestation, reforestation, degradation and regeneration for the years 1990, 2000 and 2005. Glob. Chang. Biol. 19 (4), 1173–1187.
ESRI, n.d. Cluster and Outlier Analysis (Anselin Local Moran's I). URL https://pro.arcgis.com/en/pro-app/tool-reference/spatial-statistics/cluster-and-outlier-analysis-anselin-local-moran-s.htm (accessed on 10.8.2017).
Falkowski, M.J., Wulder, M.A., White, J.C., Gillis, M.D., 2009. Supporting large-area, sample-based forest inventories with very high spatial resolution satellite imagery. Prog. Phys. Geogr. 33 (3), 403–423.
FAOSTAT, n.d. FAOSTAT. URL http://www.fao.org (accessed on 10.8.17).
Ferreira, M.P., Zortea, M., Zanotta, D.C., Shimabukuro, Y.E., de Souza Filho, C.R., 2016. Mapping tree species in tropical seasonal semi-deciduous forests with hyperspectral and multispectral data. Remote Sens. Environ. 179, 66–78.
Foody, M.G., 2002. Status of land cover classification accuracy assessment. Remote Sens. Environ. 80 (1), 185–201.
Gitelson, A.A., Kaufman, Y.J., Stark, R., Rundquist, D., 2002. Novel algorithms for remote estimation of vegetation fraction. Remote Sens. Environ. 80 (1), 76–87.
Gougeon, F.A., 1999. Automatic individual tree crown delineation using a valley-following algorithm and a rule-based system. In: Proc. Int. Forum Autom. Interpret. High Spat. Resolut. Digit. Imag. For. Victoria, British Columbia, Canada, pp. 11–23.
Gougeon, F.A., Leckie, D.G., 2006. The individual tree crown approach applied to Ikonos images of a coniferous plantation area. Photogramm. Eng. Remote. Sens. 72 (11), 1287–1297.
Hay, G.J., Castilla, G., Wulder, M.A., Ruiz, J.R., 2005. An automated object-based approach for the multiscale image segmentation of forest scenes. Int. J. Appl. Earth Obs. Geoinf. 7 (4), 339–359.
Hirschmugl, M., Ofner, M., Raggam, J., Schardt, M., 2007. Single tree detection in very high resolution remote sensing data. Remote Sens. Environ. 110 (4), 533–544.
Homolová, L., Malenovský, Z., Clevers, J.G.P.W., García-Santos, G., Schaepman, M.E., 2013. Review of optical-based remote sensing for plant trait mapping. Ecol. Complex. 15, 1–16.
Horticulture Spice Crops Clove, n.d. URL http://agritech.tnau.ac.in/horticulture/horti_spicecrops_clove.html (accessed on 11.8.17).
Huang, C.-L., Wang, C.-J., 2006. A GA-based feature selection and parameters optimization for support vector machines. Expert Syst. Appl. 31 (2), 231–240.
Huete, A.R., 1988. A soil-adjusted vegetation index (SAVI). Remote Sens. Environ. 25 (3), 295–309.
Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X., Ferreira, L.G., 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sens. Environ. 83 (1), 195–213.
Immitzer, M., Atzberger, C., Koukal, T., 2012. Tree species classification with random forest using very high spatial resolution 8-band worldView-2 satellite data. Remote Sens. 4 (9), 2661–2693.
Kaartinen, H., Hyyppä, J., Yu, X., Vastaranta, M., Hyyppä, H., Kukko, A., Holopainen, M., Heipke, C., Hirschmugl, M., Morsdorf, F., Næsset, E., Pitkänen, J., Popescu, S., Solberg, S., Wolf, B.M., Wu, J.C., 2012. An international comparison of individual tree detection and extraction using airborne laser scanning. Remote Sens. 4 (4), 950–974.
Kägi, H.U., 2008. Madagaskar: Faszination der roten Insel. (Rano-Verlag).
Koc-San, D., Selim, S., Aslan, N., San, B.T., 2018. Automatic citrus tree extraction from UAV images and digital surface models using circular Hough transform. Comput. Electron. Agric. 150, 289–301.
Kubat, M., Matwin, S., 1997. Addressing the Curse of Imbalanced Training Sets: One Sided Selection. ICML. 97. pp. 179–186.
Lackner, M., Conway, T.M., 2008. Determining land-use information from land cover through an object-oriented classification of IKONOS imagery. Can. J. Remote. Sens. 34 (2), 77–92.
Lawrence, R.L., Wood, S.D., Sheley, R.L., 2006. Mapping invasive plants using hyperspectral imagery and Breiman cutler classifications (RandomForest). Remote Sens. Environ. 100 (3), 356–362.
Leckie, D.G., Gougeon, F.A., Walsworth, N., Paradine, D., 2003. Stand delineation and composition estimation using semi-automated individual tree crown analysis. Remote Sens. Environ. 85 (3), 355–369.
Levasseur, S., Penot, E., Michel, I., Danthu, P., 2012. Document de travail AFS4FOOD, Analyse des systèmes à base de girofliers de l'Ile Ste Marie, à Madagascar.
Lin, C., Wu, C., Tsogt, K., Ouyang, Y., Chang, C., 2015. Effects of atmospheric correction and pansharpening on LULC classification accuracy using WorldView-2 imagery. Inf. Process. Agric. 2 (1), 25–36.
Lobell, D.B., Thau, D., Seifert, C., Engle, E., Little, B., 2015. A scalable satellite-based crop yield mapper. Remote Sens. Environ. 164, 324–333.
Lobietti, M., 2013. Analyse des systèmes girofliers à Fénérive-Est, Madagascar: dynamiques spatiales, trajectoires et stratégies paysannes. Cirad.
Locatelli, B., 2000. Pression démographique et construction du paysage rural des tropiques humides: l'exemple de Mananara (Madagascar). ENGREF (AgroParisTech).
Mahour, M., Tolpekin, V., Stein, A., 2016. Tree detection in orchards from VHR satellite images using scale-space theory. Proc. SPIE 10004.
Maistre, J., 1964. Les plantes à épices, Techniques agricoles et productions tropicales. Maisonneuve & Larose.
Mallinis, G., Koutsias, N., Tsakiri-Strati, M., Karteris, M., 2008. Object-based classification using Quickbird imagery for delineating forest vegetation polygons in a Mediterranean test site. ISPRS J. Photogramm. Remote Sens. 63 (2), 237–250.
Michels, T., Bisson, A., Ralaidovy, V., Rabemananjar, H., Jahiel, M., Malézieux, E., 2011. Horticultural agroforestry systems in the humid tropics: analysis of clove tree-based systems in Madagascar. Acta Hortic. (894), 161–168.
Ministère des Affaires étrangères, 2012. Mémento de l'Agronome. Cirad. Éd. Ministère des affaires étrangères, pp. 1077–1078.
Nagayets, O., 2005. Small farms: current status and key trends. In: Future of Small Farms, pp. 355–367.
Nellis, M.D., Price, K.P., Rundquist, D., 2009. Remote sensing of cropland agriculture. In: The SAGE Handbook of Remote Sensing. 1. pp. 368–380.
Ørka, H.O., Næsset, E., Bollandsås, O.M., 2009. Classifying species of individual trees by intensity and structure features derived from airborne laser scanner data. Remote Sens. Environ. 113 (6), 1163–1174.
Pal, M., 2005. Random forest classifier for remote sensing classification. Int. J. Remote Sens. 26 (1), 217–222.
Pollock, R.J., 1996. The Automatic Recognition of Individual Trees in Aerial Images of Forests Based on a Synthetic Tree Crown Image Model. The University of British Columbia.
Pouliot, D.A., King, D.J., Bell, F.W., Pitt, D.G., 2002. Automated tree crown detection and delineation in high-resolution digital camera imagery of coniferous forest regeneration. Remote Sens. Environ. 82 (2), 322–334.
Pushparaj, J., Hegde, A.V., 2017. Evaluation of pan-sharpening methods for spatial and spectral quality. Appl. Geomatics 9 (1), 1–12.
Rizon, M., Yazid, H., Saad, P., Md Shakaff, A.Y., Saad, A.R., Sugisaka, M., Yaacob, S., Mamat, M.R., Karthigaya, M., 2005. Object detection using circular Hough transform. Am. J. Appl. Sci. 2, 1606–1609.
Rodriguez-Galiano, V.F., Ghimire, B., Rogan, J., Chica-Olmo, M., Rigol-Sanchez, J.P., 2012. An assessment of the effectiveness of a random forest classifier for land-cover classification. ISPRS J. Photogramm. Remote Sens. 67, 93–104.
Rouse, J.W., Hass, R.H., Schell, J.A., Deering, D.W., 1973. Monitoring vegetation systems in the great plains with ERTS. Third Earth Resour. Technol. Satell. Symp. 1, 309–317.
Shang, X., Chisholm, L., 2014. Classification of Australian native forest species using hyperspectral remote sensing and machine-learning classification algorithms. IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens. 7 (6), 2481–2489.
Srestasathiern, P., Rakwatin, P., 2014. Oil palm tree detection with high resolution multispectral satellite imagery. Remote Sens. 6 (10), 9749–9774.
Stibig, H., Achard, F., Carboni, S., Raši, R., Miettinen, J., 2014. Change in tropical forest cover of Southeast Asia from 1990 to 2010. Biogeosciences 11 (2), 247–258.
The MathWorks Inc, 2006. MATLAB Graycomatrix. URL. https://ch.mathworks.com/help/images/ref/graycomatrix.html, Accessed date: 8 October 2017.
The MathWorks Inc, 2009. MATLAB Treebagger. URL. https://ch.mathworks.com/help/stats/treebagger.html, Accessed date: 8 October 2017.
The MathWorks Inc, 2012. MATLAB Imfindcircles. URL. https://ch.mathworks.com/help/images/ref/imfindcircles.html, Accessed date: 8 October 2017.
The MathWorks Inc, 2013. MATLAB extractHOGFeatures. URL. https://ch.mathworks.com/help/vision/ref/extracthogfeatures.html, Accessed date: 8 October 2017.
The USGS Land Cover Institute (LCI), n.d. Land Cover Institute (LCI). URL https://

landcover.usgs.gov/classes.php (accessed on 9.8.17).
Thomson, A., 2016. An Introduction to African Politics. Routledge.
Tuia, D., Camps-Valls, G., Matasci, G., Kanevski, M., 2010. Learning relevant image features with multiple-kernel classification. IEEE Trans. Geosci. Remote Sens. 48 (10), 3780–3791 art. no. 5497137.
Tuominen, S., Haapanen, R., 2011. Comparison of grid-based and segment-based estimation of Forest attributes using airborne laser scanning and digital aerial imagery. Remote Sens. 2011 (3), 945–961.
Wang, L., 2010. A multi-scale approach for delineating individual tree crowns with very high resolution imagery. Photogramm. Eng. Remote. Sens. 76 (4), 371–378.
Watts, J., Lawrence, R., 2008. Merging random forest classification with an object-oriented approach for analysis of agricultural lands. Int. Arch. Photogramm. Remote. Sens. Spat. Inf. Sci. 37, 2006–2009.
Wolf, B.M., Heipke, C., 2007. Automatic extraction and delineation of single trees from remote sensing data. Mach. Vis. Appl. 18 (5), 317–330.
Wulder, M.A., White, J.C., Niemann, K.O., Nelson, T., 2004. Comparison of airborne and satellite high spatial resolution data for the identification of individual trees with local maxima filtering. Int. J. Remote Sens. 25 (11), 2225–2232.
Zhang, Q., Wang, J., 2003. A rule-based urban land use inferring method for fine-resolution multispectral imagery. Can. J. Remote. Sens. 29 (1), 1–13.
Zhang, X., Xiao, P., Feng, X., Wang, J., Wang, Z., 2014. Hybrid region merging method for segmentation of high-resolution remote sensing images. ISPRS J. Photogramm. Remote Sens. 98, 19–28.